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# DETERMINATION OF THE RELATIVE MAGNETIC PERMEABILITY BY USING AN ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM AND 2D-FEM

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**Abstract**—Adaptive Neuro-fuzzy systems constitute an intelligent systems hybrid technique that combines fuzzy logic with neural networks in order to have better results. A study is presented to forecast the relative magnetic permeability using ANFIS. The global electromagnetic parameter, namely, the magnetic induction has been used as input to estimate the relative magnetic permeability. In this exceptional research, finite element simulations are carried out to build up a database which will be used to train ANFIS network. The ANFIS approach learns the rules and membership functions from training data. The hybrid system is tested by the use of the validation data. Performance of the trained ANFIS network was compared with the multilayer feed forward network model and experimental results. The results show the effectiveness of the proposed approach in solving inverse electromagnetic problem.

## 1. INTRODUCTION

A variety of installations for discovering the physical properties of materials under test from the measured values have been proposed [1–4]. We can apply the neural network to obtain these materials. The neural models are most effective approximator of functions in industry applications because it has the ability to solve difficult nonlinear problems. Neural network performance is reliant on the quality and quantity of training samples presented to the network [1]. Sometimes,

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when the training data set is not fully representative of the possibility space, exploitation of fuzzy systems improves performance [2].

In recent years, the fuzzy system has been applied in numerous of fields, such as power system, industry's control [2]. Neuro-fuzzy systems constitute an intelligent systems hybrid technique that combines fuzzy logic with neural networks in order to have better results. ANFIS can be described as a fuzzy system equipped with a training algorithm. It is quite quick and has very good training results that can be compared to the best neural networks. Neuro-fuzzy network have been widely used for many different industrial areas such as control, modelling, prediction, identification, pattern recognition [2, 3]. Neuro-fuzzy system represents connection of numerical data and linguistic representation of knowledge. The neuro-fuzzy system works similarly to that of multi-layer neural network. This hybrid system uses the adaptive neural networks (ANNs) theory to characterize the input-output relationship and build the fuzzy rules by determining the input structure. Several approaches have been proposed to generate fuzzy rules, from training data, based on Takagi-Sugeno-Kang-type fuzzy model. One such an approach is called the adaptive-network-based fuzzy inference system (ANFIS). ANFIS is a class of adaptive multi-layer feed-forward network that is functionally equivalent to a fuzzy inference system. The Adaptive network based fuzzy inference system (ANFIS) model was proposed by Jang in 1993 [2] as a basis for constructing a set of fuzzy rules with appropriate membership functions from a set of input-output examples. This model has been a source of inspiration for many other fuzzy models defined in more recent works [2, 3].

Generally, the ANFIS has a capability to approach several nonlinear unknown systems. In this work, we are going to exploit ANFIS to forecast a material unknown. ANFIS is presented so as to generate an excellent estimation to the nonlinear correlation between the relative permeability and the magnetic induction at sensor position. A large number of specimens with different relative permeability are simulated using the 2D-FEM for calculating the detected signal of the magnetic induction. The paired data with the form of (detected signal of the magnetic induction, relative permeability) are collected from these obtained results for ANFIS model.

## 2. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

The abbreviation ANFIS derives its name from adaptive neuro-fuzzy inference system. Using a given input-output data set, ANFIS build a fuzzy inference system (FIS) whose membership function parameters

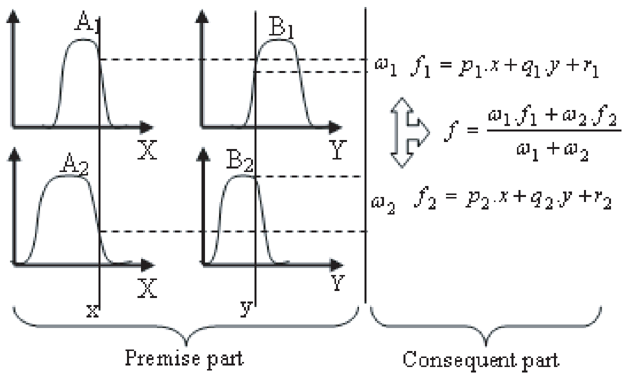


**Figure 1.** Sugeno fuzzy if-then rule and fuzzy reasoning mechanism.

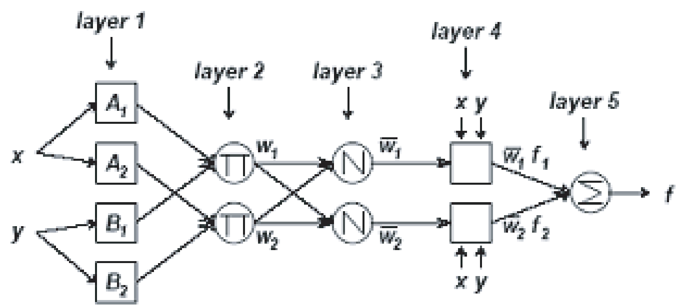


**Figure 2.** The general architecture of ANFIS [2, 3].

are adjusted through the learning process. This hybrid system is generally based on the Takagi-Sugeno's fuzzy If-Then rules as shown in Fig. 1. It involves a premise part and consequent part. The Takagi-Sugeno fuzzy system has less linguistic power when compared with a Mamdani fuzzy system, since the consequents are not represented with meaningful linguistic terms [5]. Fig. 2 illustrates ANFIS architecture for Takagi-Sugeno type fuzzy inference system, where nodes of the identical layer have the same functions.

In general, neuro-fuzzy system has input and output layers, and three hidden layers that represent membership functions and fuzzy rules. Each node in a layer receives input signals from a previous layer and transmits its output signals to nodes in the next layer. In the adaptive network, we use both circle (fixed nodes) and square nodes (adaptive nodes). Adaptive nodes have parameter sets while fixed nodes have none. The parameter sets are computing according to given training data and a learning procedure for complete a desired input-output data set. By varying these parameters, we are really changing the node function (adaptive nodes) and the behavior of adaptive network. To explicate the procedure of the trained ANFIS network, we consider two inputs $x$ and $y$ and one output $f$ in ANFIS. For the first-order Sugeno inference system, typical two rules can be expressed as:

Rule 1: if $x$ is $A_1$ and $y$ is $B_1$ then $f_1 = p_1 \times x + q_1 \times y + r_1$

Rule 2: if $x$ is $A_2$ and $y$ is $B_2$ then $f_2 = p_2 \times x + q_2 \times y + r_2$

where $x$ and $y$ the inputs variables to the node $i$, $A_i$ and $B_i$ are fuzzy sets (or the linguistic table), which are characterized by convenient membership functions and finally, $p_i$, $q_i$ and $r_i$ are the consequence parameters. The structure of this inference system is shown in Fig. 2.

Layer 1: Each node in this first layer is adjustable node. The output signals are the fuzzy membership functions of the input signals, which are given by the node function as:

$$\begin{array}{ll} O_i^1 = \xi_{A_i}(x), & i = 1, 2 \\ O_i^1 = \xi_{B_{i-2}}(y), & i = 3, 4 \end{array} \tag{1}$$

where $A_i$ and $B_{i-2}$ is the linguistic variable. The fuzzy membership function is generally chosen as a generalized bell-shape with upper limit and lower limit equal to 1 and 0. The generalized bell-shape function depends on three parameter sets $a$, $b$, and $c$ as given by:

$$\xi(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}} \tag{2}$$

where the parameter $b$ is usually positive. The parameter $c$ locates the centre of the curve. The parameter sets in this first layer are named as premise parameters.

Layer 2: all nodes in this layer are not adaptive (fixed node, labelled as $\pi$). Each node calculates the firing strength of a rule $w_i$ or the output signal through multiplication:

$$O_i^2 = t\left(\xi_{A_I}(x), \xi_{B_{i-2}}(y)\right) = \xi_{A_i}(x) \cdot \xi_{B_{i-2}}(y) = \omega_i \tag{3}$$

Layer 3: In this layer, every node isn't also adaptive. Nodes in the third layer (labelled as $N$) compute the normalized firing strength $w_i$ by dividing each rule firing strength by the summation of all of them. The output signals can be represented as:

$$O_i^3 = \bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2} \tag{4}$$

Layer 4: Nodes (adjustable node) in this layer compute the weighted output of the rules by evaluating the Takagi-Sugeno type linear approximator $f_i$ multiplied by the normalized firing strength:

$$O_i^4 = \bar{\omega}_i \cdot f_i = \bar{\omega}_i \left(p_i \cdot x + q_i \cdot y + r_i\right) \tag{5}$$

Layer 5: This layer has only one node labelled $S$ that is a fixed node. The output of the system is computed by the node in the last layer as a summation of all incoming signals. Hence, the global output signal of the node is given by:

$$O_i^5 = \sum_i \bar{\omega}_i f_i = \frac{\sum\limits_i \omega_i \cdot f_i}{\sum\limits_i \omega_i} \tag{6}$$

For the hybrid neuro-fuzzy system or the ANFIS, suppose that the ANFIS has only one global output represented by:

$$output = F\left(I, S\right) \tag{7}$$

where $I$ is the set of input variables. For this overall output, we can divide the parameter set $S$ into two sets $S_1$ (premise parameters) and $S_2$ (consequent parameters). In this case, the total parameter is $S_1 \oplus S_2$, where $\oplus$ is the direct sum of the two parameters.

In the forward pass of the hybrid ANFIS; the consequent parameters are identified by the least-squares algorithm. However for the backward pass, the error signals propagate backward and by descent method [6] we can calculate (or update) the premise parameters with respect the overall error measure (cost function for training):

$$E = \sum_{p=1}^{P} E_p = \sum_{p=1}^{P} \sum_{m=1}^{N(L)} \left(T_{m,p} - O_{m,p}^L\right)^2 \tag{8}$$

where $T_{m,p}$ is the $m$th component of the $p$th target output vector, and $O_{m,p}$ is the $m$th component of the actual output vector produced by the $p$th input vector, $P$ is the number of the training vectors. The partial derivative depends on the type of membership function (MF) used. In this case, the gradient is used to update the MF parameters $\alpha$, then:

$$\frac{\partial E}{\partial \alpha} = \sum_{p=1}^{P} \frac{\partial}{\partial \alpha} \sum_{m=1}^{N(L)} \left(T_{m,p} - O_{m,p}^L\right)^2 \tag{9}$$

And the update parameter vector is:

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha} \tag{10}$$

The learning rate can be written:

$$\eta = \frac{k}{\sqrt{\sum_{\alpha} \left(\frac{\partial E}{\partial \alpha}\right)^2}} \tag{11}$$

where $k$ is the step size, which can be changed to vary the speed of convergence. The type of membership functions (MFs) of the inputs are generalized bell function, which contains three fitting parameters $a$, $b$ and $c$. A hybrid learning algorithm (gradient method and least square estimate) is proposed to fine tune the values of these parameters. If these parameters are fixed, the output of the whole network system becomes:

$$\begin{aligned} f &= \frac{\omega_1}{\omega_1+\omega_2} f_1 + \frac{\omega_1}{\omega_1+\omega_2} f_2 \\ &= (\bar{\omega}_1 \cdot x)\, p_1 + (\bar{\omega}_1 y)\, q_1 + (\bar{\omega}_1)\, r_1 + (\bar{\omega}_2 x)\, p_2 + (\bar{\omega}_2 y)\, q_2 + (\bar{\omega}_2)\, r_2 \end{aligned} \tag{12}$$

This is a linear combination of the modifiable parameters $p_1$, $q_1$, $r_1$, $p_2, q_2$, $r_2$.

## 3. DATA PREPARATION

### 3.1. Description of the System

The test configuration chosen for the evaluation of the new trained ANFIS model is shown in Fig. 3. This Benchmark problem was planned by the Japan Society of Applied Electromagnetics and Mechanics [6] for the characterization of ferromagnetic properties such as relative magnetic permeability and electric conductivity.

Figure 3 shows the description of this difficult problem in NDE. The relative magnetic permeability in the materials under test will be identified from the detected signal of the magnetic induction (the detected signal is calculated by the following equation: DB $= B/B_0$, where $B$ and $B_0$ are the magnetic induction with and without material under control) at the sensor position. The problem consists of E-shaped ferrite core, excited by two coaxial coils (bobbin) and in the presence of a material under control. In this problem, the bobbin is supplied by a current source with constant amplitude $Ic$ (Here is 0.1 A).

The physical parameters used in the electromagnetic field computation are relative permeability ($\mu_r = 1$ for coil and air, $\mu_r \in [50,\ 1000]$ for material under test, $\mu_r = 1100$ for magnetic core), conductivity of all space ($\sigma = 5.7\text{e}7\,\text{S/m}$ for coil (copper) and $\sigma = 1\text{e}6\,\text{S/m}$ for a material under test), air gap is 0.1 mm. The material under control is a magnetic material of 5 mm height and 200 mm width. The simplified model of the probe-specimen is shown Fig. 4.

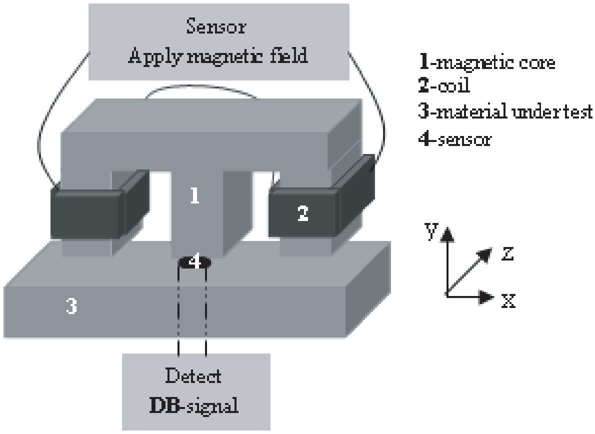


**Figure 3.** Probe-material under test configuration.

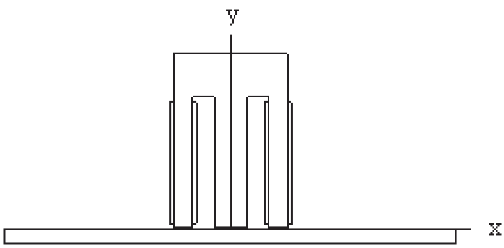


**Figure 4.** Example of typical joining application.

### 3.2. Finite Element Method

From Maxwell's equation, we calculate the magnetic field from the magnetic vector potential. The differential form of Maxwell's equation can be expressed as:

$$\nabla \times H = J \tag{13}$$

$$\nabla \cdot B = 0 \tag{14}$$

$$\nabla \times E = -\frac{\partial B}{\partial t} \tag{15}$$

where $\nabla$ is the Laplace operator, $H$ is the magnetic field, $B$ the magnetic induction, $J$ the electrical current density and $E$ is the electrical field. For two dimensional problems, the magnetic vector potential $A$ is the obvious choice in most instances. The divergence condition on $B$ implies the existence of a vector potential defined by:

$$B = \nabla \times A \tag{16}$$

The magnetic field of electromagnetic model can be considered as a magnetostatic problem. Substituting (16) to (13) we obtain:

$$\nabla \times \left( \frac{1}{\mu} \nabla \times A \right) + \sigma \frac{\partial A}{\partial t} = J \tag{17}$$

where $\mu$ is the magnetic permeability, $\sigma$ is the electric conductivity.

The finite element method is one of the most numerical methods used to solve this differential equation. The FEM is widely used by scientists and engineers. In this method, the equation is discretized in space by the Galerkin's method. After discretization of the domain, the vector potential has been approximated using first-order triangular elements. In each element, the vector potential varies according to:

$$A = \sum_{i=l,m,n} A_i N_i \tag{18}$$

where $A_i$ are the node values of $A$ and $N_i$ are first order polynomials. Applying the Galerkin's method to Eq. (17), we have:

$$\int_s N^t \left[ \frac{\partial}{\partial x} \nu \frac{\partial A}{\partial x} + \frac{\partial}{\partial y} \nu \frac{\partial A}{\partial y} \right] dxdy + jw \int_s \sigma N_i^t N_j A dxdy + \int_s N^t J dxdy = 0 \tag{19}$$

where $\nu$ is the magnetic reluctivity.

After assembling all the elementary equations, an algebraic system of equations is obtained which may be written as:

$$([M] + jw[K])\,[A] = [F] \tag{20}$$

where $([M] + jw\,[K])$ is the global coefficient matrix, $[A]$ is the matrix of nodal magnetic vector potentials and $[F]$ is nodal currents (forcing functions) which are given by:

$$M_{ij} = \int_{s_i} \nu \nabla N_i \nabla N_j dxdy \tag{21}$$

$$K_{ij} = \int_{s_i} \sigma N_i^t N_j^d xdy \tag{22}$$

$$F_i = \int_{s_i} J N_i^t dxdy \tag{23}$$

The Gaussian elimination algorithm is then used to solve the above banded matrix equation. The field solution is used to calculate the magnetic induction. More details about the finite element method can be found in [7].

### 3.3. Training and Testing Data

The forward problem predicts the DB at sensor position with more excitation frequencies using the 2D-finite element method from the magnetic potential vector **A**. The main reason for the selection of 2D-FEM is related to their wide area of use and good global electromagnetic properties. In 2D-FEM the regions are meshed and the DB is the unknown vector in the sensor position. The mesh is automatically generated by dividing the geometry into discrete elements. Standard triangular elements are applied here. The open boundary was set at a radius of $4 \times l$ (where $l$ is the length of material under test) using the Dirichlet condition. The generated mesh had approximately 7294 nodes or 14484 first order triangular elements. It is essential to select an adequate mesh to characterize precisely the electromagnetic phenomena and then, to reduce the numerical errors that can influence the convergence of the identification process.

The data set used in this study is obtained using a 2D-FEM. The partial differential equation toolbox (PDE-toolbox) [8] for the 2D-FEM is used in measurements and the finite element meshes generation. The problem was solved on a PC with P4 2.4G® CPU under Matlab 7 workspace. In order to generate the database for training of the ANFIS model, 2D-FEM simulations will be carried out for diverse sets of material parameters.

Through the stage of 2D-FEM simulations, errors can appear due to its particularly character [9, 10]. Accordingly, the results of the 2D-FEM must be carefully examined. To verify the database, we will plot a few values of relative permeability in the same figure. The detected signal of the magnetic induction (DB) are calculated at nine different frequencies (61–610 Hz, one every 30.5 Hz) using finite element method at the sensor position. Fig. 5 shows the DB in the region of the device at the sensor position for five materials having the different relative permeability. By these results of the 2D-FEM simulations, the test of coherence of the data set is verified and gives us that not errors in the data set.

For the preparation of the learning, 130 sets of relative permeability $\mu = 50, 57.364, \ldots, 1000$ (step size = 7.364) are exploited. Initially it is appropriate to split the data to training and test data. The 130 cases are used for the DB calculation. Some of the obtained values (50%) are used in training of ANFIS model and the rest is used in testing (50%).

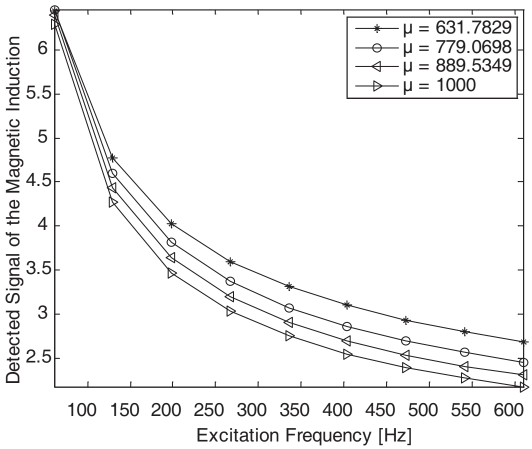


**Figure 5.** The DB as a function of frequency for different relative magnetic permeability.

## 3.4. Identification Strategy

In this paper, we present a new technique on the use of the ANFIS and 2D-FEM in the relative magnetic permeability identification. The new methodology can be summarized as follows:

1) A large number of specimens with different relative permeability are simulated using the 2D-FEM for the DB calculation.

2) The paired data with the form of ([detected signal of the magnetic induction at all frequencies; relative permeability]) are collected from these obtained results for ANFIS model.

3) The collected data are used to train the ANFIS to approximate the functional relations between input variables (DB) and responses (relative permeability) to a desired degree of accuracy.

4) The trained ANFIS network is then tested with the new relative permeability (testing data) of the specimens, which not belong to the original data set.

# 4. RESULTS AND DISCUSSION

All of the relative magnetic permeability data are arranged for 9-input-1-output system as this format: ([DB(f1); DB(f2); DB(f3); DB(f4); DB(f5); DB(f6); DB(f7); DB(f8); DB(f9), relative permeability]), where, for the first vector, DB are the inputs values and relative permeability is the output variable.

For our identification approach, the data set is partitioned into a training set and a checking set. For reduce the CPU time of the inverse problem, in the first, we perform a new forward search within the available inputs to select the two inputs that generally influence the relative magnetic permeability. The target of this strategy is the specification of the number of input combinations during the search. In trained ANFIS network, the aim was reducing the root mean square error, which defines as: $(1/2P) \times E$ (see (8)).

For our problem, there are 9 input candidates ([DB(f1); DB(f2); DB(f3); DB(f4); DB(f5); DB(f6); DB(f7); DB(f8); DB(f9)]), and the output to be expected is relative magnetic permeability. First of all, we construct nine ANFIS models for select the one most influential input attribute in the output. In the second step, we build eight ANFIS models with various input combinations, and select the two most influential inputs attribute in the relative magnetic permeability. The result is shown in the plot (see Fig. 6), where 2 inputs ([DB(f1); DB(f4)]) are selected with a training RMSE of 0.4688 and checking RMSE of 0.8375.

In Fig. 6, we can see that ANFIS with DB(f1) and DB(f4) as inputs has the least error, so it is logical to select these new inputs for further parameter tuning. The results from this strategy indicate that DB(f1) and DB(f4) form the optimal combination of two input attributes.

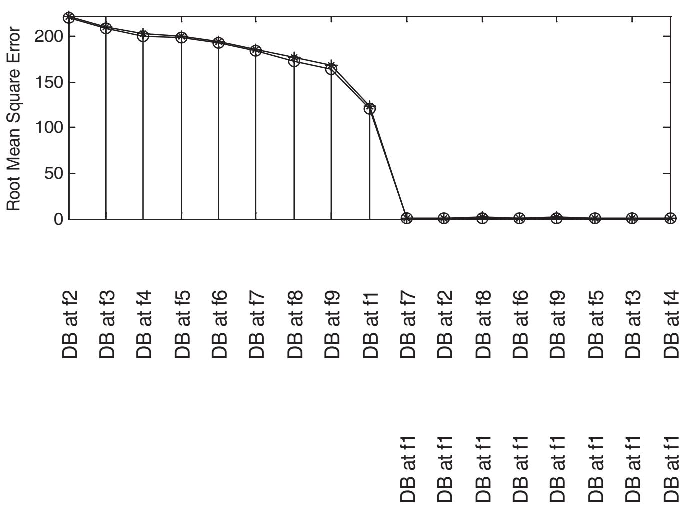


**Figure 6.** Input variable combinations and their influence (Training (Circles), Checking (Asterisks)).

By this new strategy for input selection in NDE, we then extract the selected input attributes from the original training and checking data set (this approach is used for reducing the time calculation of the inverse approach).

The ANFIS system is started with new candidate inputs data set (the detected signal of the magnetic induction DB at two frequencies) in the [DB(f1); DB(f4)] format. Next, the steps of our approach are: 1) The paired data with the new form of ([DB(f1); DB(f4)]) are given to the trained ANFIS network. 2) The trained ANFIS network completes the forward pass which the overall output $f$ is the relative magnetic permeability. 3) After training phase the trained ANFIS system is tested with another independent data. 4) The error is calculated for every one epoch by computing the root mean square errors. 5) Training of the ANFIS is performed using both least squares method and back-propagation. In the forward pass the consequent parameters ($pi$, $qi$ and $ri$) are updated using least squares and in the backward pass the premise parameters ($ai$, $bi$ and $ci$) are identified using back-propagation. This is offline learning, because the trained ANFIS network accepts all data sets. Also, all parameters are updated. 6) After these steps calculation, if the number of ANFIS training epochs is achieved then the system terminates.

The bell-shape membership function is adopted in the ANFIS training. The number of MFs for the input variables DB(f1) and DB(f4) is five and five, respectively. The ANFIS model is formed by twenty-five ($5 \times 5 = 25$) fuzzy rules with linear sequences whose

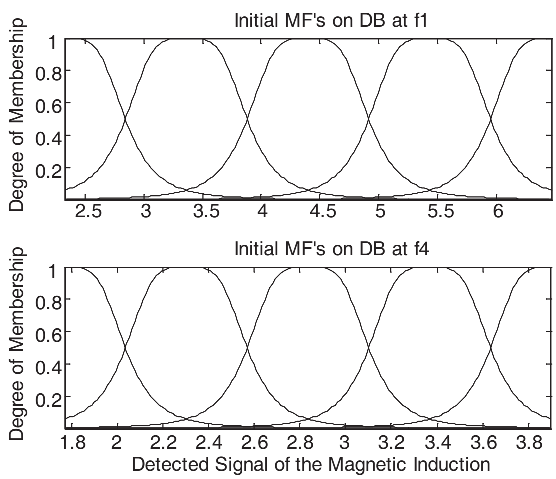


**Figure 7.** Initial bell-shaped membership function.

it's membership functions are represented by the Fig. 7. Hence, the ANFIS used here contains a total of ninety-five fitting parameters, of which twenty ($5 \times 2 + 5 \times 2 = 20$, here 2 is the input variables) are the premise parameters and seventy-five ($3 \times 25 = 75$, here 3 is the number of the unknown consequent parameters) are the consequent parameters.

The rules (Ri) of the this model are defined by:

(R1) IF (DB(f1) is VS) AND (DB(f4) is VS)
THEN $\mu = p_1 \cdot \text{DB(f1)} + q_1 \cdot \text{DB(f4)} + r_1$

(R2) IF (DB(f1) is VS) AND (DB(f4) is SM)
THEN $\mu = p_2 \cdot \text{DB(f1)} + q_2 \cdot \text{DB(f4)} + r_2$

(R3) IF (DB(f1) is VS) AND (DB(f4) is ME)
THEN $\mu = p_3 \cdot \text{DB(f1)} + q_3 \cdot \text{DB(f4)} + r_3$

(R4) IF (DB(f1) is VS) AND (DB(f4) is VS)
THEN $\mu = p_4 \cdot \text{DB(f1)} + q_4 \cdot \text{DB(f4)} + r_4$

(R5) IF (DB(f1) is VS) AND (DB(f4) is VL)
THEN $\mu = p_5 \cdot \text{DB(f1)} + q_5 \cdot \text{DB(f4)} + r_{5\ldots}$

(R23) IF (DB(f1) is VL) AND (DB(f4) is ME)
THEN $\mu = p_{23} \cdot \text{DB(f1)} + q_{23} \cdot \text{DB(f4)} + r_{23}$

(R24) IF (DB(f1) is VL) AND (DB(f4) is LG)
THEN $\mu = \mathrm{p}_{24} \cdot \text{DB(f1)} + q_{24} \cdot \text{DB(f4)} + r_{24}$

(R25) IF (DB(f1) is VL) AND (DB(f4) is VL)
THEN $\mu = p_{25} \cdot \text{DB(f1)} + q_{25} \cdot \text{DB(f4)} + r_{25}$

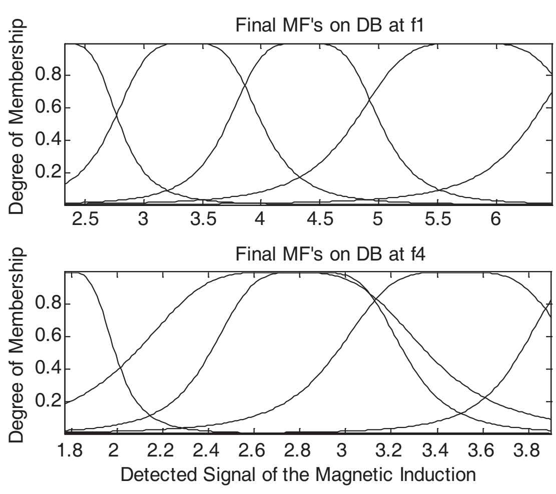


**Figure 8.** Final bell-shaped membership function.

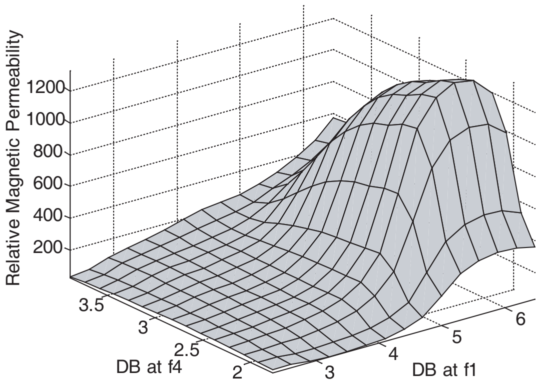


**Figure 9.** Input-Output surface for trained ANFIS (testing data).

**Table 1.** Rmse and average percent rmse of training and testing data.

| RMSE of training data | RMSE of testing data | Average percent RMSE of training data | Average percent RMSE of testing data |
|---|---|---|---|
| 4.8488e-3 | 1.5181e-2 | 6.3068e-4 | 4.7953e-3 |

Five types of fuzzy sets are used for indicating "very small", "small", "medium", "large" and "very large" respectively. Fig. 7 illustrates their MFs, and each with three control parameters: the center of MFs $c$ and the interval range of target variable $[a, b]$. Also, each fuzzy value such as VS is denoted by the control parameters $p$, $q$ and $r$. These parameters are used in computing the output of the ANFIS system separately. Fig. 8 illustrates the final membership functions for each input variable. The input-output surface of the ANFIS model is shown in Fig. 9. The input-output surface shown above is a nonlinear surface and illustrates how the ANFIS model will respond to varying values of DB. The trained ANFIS network was used to approximate the functional relations between input variables (DB(f1) and DB(f4)) and responses (relative magnetic permeability) to a desired degree of accuracy.

The ANFIS models shown in Fig. 9 was implemented by using Matlab® Fuzzy Logic Toolbox [11], it uses training data and the step size for parameter adaptation had an initial value of 0.2. Training was executed off-line for the solution. The steps of parameter adaptation of the ANFIS are shown in Fig. 10.

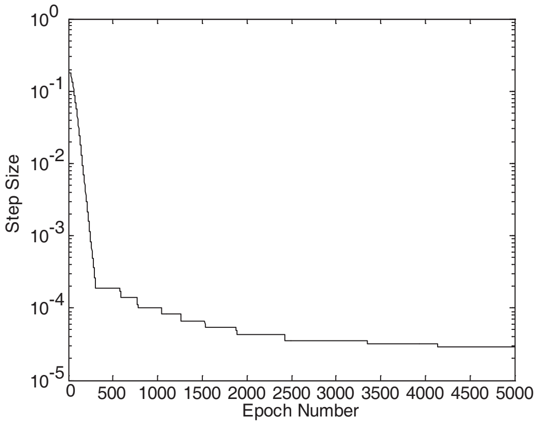


**Figure 10.** Parameter step adaptation.

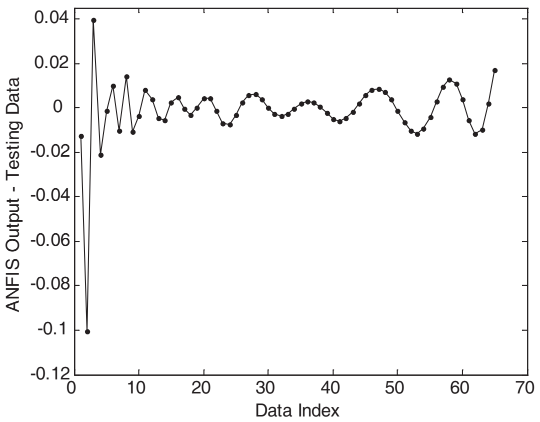


**Figure 11.** Errors between the ANFIS output and testing data.

Root mean square errors and average percentage mean square errors of training and testing results of ANFIS model which is trained for 5000 epochs, are tabulated in Table 1. Fig. 11 illustrate the errors between ANFIS output and the independent data set (testing data) for evaluating trained ANFIS network. Good agreement between the two data sets proves that ANFIS has learned well the behavior of the identification process. The real error values of evaluation data set revealed that the training ANFIS network was done without any over-training [6]. At 5000 training periods for ANFIS, the network error convergence curve was derived as shown in Fig. 12. From this

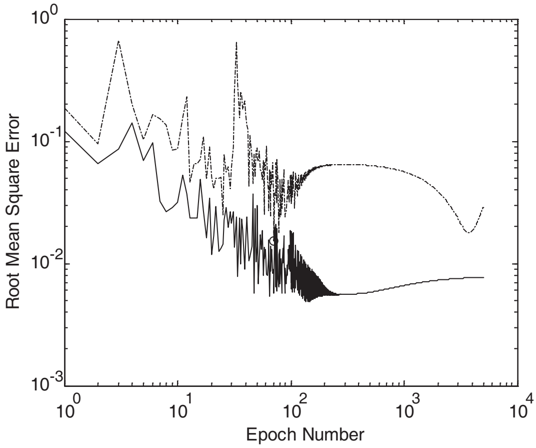


**Figure 12.** ANFIS training (solid line) and checking (dashed line) errors.

curve, the final convergence value is 4.8488e-3. The minimal checking error occurs at about epoch 71 for ANFIS, which is indicated by a circle. Notice that the checking error curve goes up after 71 epochs, indicating that further training overfits the data and produces worse generalization (See Fig. 12).

In the following study, identification of relative magnetic permeability of material under test using multi-layer neural network [1, 10, 12, 13] will be realize with the same data set which are used in this other learning process. Numerical data set were used to train trained MLP network, which have nine inputs ([DB(f1); DB(f2); DB(f3); DB(f4); DB(f5); DB(f6); DB(f7); DB(f8); DB(f9)]) and one output ([relative magnetic permeability]). Next, the trained MLP network was tested periodically using data not used in the training phase. In this work, the number of hidden layers and units was established by training a different rang of networks and selecting the one that best balanced generalization performance against network size. Therefore, a shape of nine input neurons, a single hidden layer with ten neurons and output layer with one neuron, noted MLP (9-10-1) was used. For this trained MLP network; the hidden neurons use a hyperbolic tangent sigmoids as nonlinear activation functions. Good identification is obtained with the MLP (9-10-1), on training data: RMSE of 9.0124e-2 for relative magnetic permeability. In general, neural network exploit the back-propagation process [12–14] but ANFIS use hybrid method for training fuzzy inference membership function parameters.

**Table 2.** Results Obtained From anfis and mlp models.

| Models | ANFIS model | MLP model |
|---|---|---|
| No. of Input parameter | 2 | 9 |
| Training RMSE | 4.8488e-3 | 9.0124e-2 |
| Testing RMSE | 1.5181e-2 | 1.2586e-1 |
| CPU time | 45 s | 536 s |

**Table 3.** The experimental and identified material parameter for the two network models.

| Relative Permeability | experimental values [7] | ANFIS model | MLP model |
|---|---|---|---|
| $\mu 1$ | 250 | 250.5211 | 252.5619 |
| $\mu 2$ | 500 | 500.3351 | 501.0123 |
| $\mu 3$ | 1000 | 1000.103 | 1002.256 |

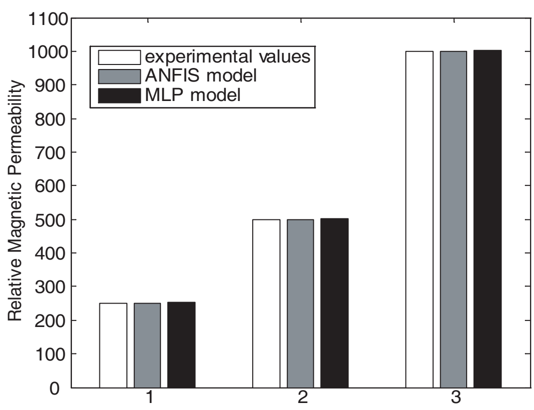


**Figure 13.** Experimental and network models results.

The Table 2 is a comparison among the two approaches. The MLP spends the largest amount of time to reach the final solution, which the trained ANFIS network via a new forward search takes the least amount of time to reach the best accuracy. In these results, if the precision is a goal, we can remark that ANFIS has the highest precision.

Table 3 and Fig. 13 show the comparison between the experimental results and the identified relative magnetic permeability parameter using these approaches. Fig. 13 shows that a very good agreement between experiment and inverse strategies is obtained for this difficult eddy current problem. These results confirm that the trained ANFIS model is accurate and expert for solving materials properties determination inverse problem of non-destructive evaluation.

## 5. CONCLUSION

Measurement of relative magnetic permeability of metallic walls requires specialized laboratories [1, 13]. It is for this reason that new approach for solving inverse problem has been used by some authors to evaluate the physical property of metallic walls. In this paper we propose a new approach based on the use of the 2D-FEM and ANFIS model for the parameter identification of materials under test. The ANFIS is presented so as to create an excellent relationship between the ferromagnetic properties and the detected signal of the magnetic induction. It is concluded that ANFIS model is more efficient to multi-layer neural network (MLP) for solving inverse electromagnetic problem.

In conclusion, the obtained results demonstrate that the FEM-ANFIS presented in this study can be used as another way to identify the ferromagnetic properties of pieces under test.

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